HEALTH MONITORING AND CONTINUOUS COMMISSIONING OF CENTRIFUGAL CHILLER SYSTEMS

Jingtan Cui and Shengwei Wang

Department of Building Services Engineering, The Hong Kong Polytechnic University

Summary: This paper presents strategies for detecting and diagnosing the chiller component faults and the sensor faults involved in chiller conditioning monitoring and control. The two strategies are used in series. One strategy diagnoses and validates the sensor faults. After the sensor faults are validated, the other strategy monitors the health condition and diagnoses the faults of chiller components. The health monitoring and diagnosis of the sensors are conducted using PCA (Principle Component Analysis) method. The chiller component condition monitoring and diagnosis is conducted based on the reference models of six performance indexes and an online threshold generator updating the fault detection thresholds following the change of working conditions. The paper also presents the validation of the two strategies using the field data of the BMS in a large office building.

Keywords: health monitoring, fault diagnosis, component fault, sensor fault, chiller system, PCA, performance index, threshold estimation

1. INTRODUCTION

Chiller systems, the most important and expensive piece of equipment in HVAC systems, account for a large portion of energy consumption of HVAC system in buildings. In large office buildings, it is estimated that the electricity consumption of chillers is typically 35-40% of the total building energy consumption for commercial buildings in Hong Kong. With the advance in networking technologies and standard protocols, chiller system can be convenient integrated into Building Management Systems (BMS) to achieve automatic chiller monitoring and optimal control of the entire HVAC&R system. During operation, chiller performance is heavily affected by ever-changing environmental conditions, e.g., outdoor air temperature and humidity. In addition, chiller component faults may occur in the course of operation, which can result in a great waste of energy consumption, complaints from occupants and shortened equipment life. Therefore, there is a great need to develop automatic component fault detection and diagnosis (FDD) and optimal control. There are many papers pertinent to FDD of chiller systems (Gordon and Ng. 1995, Peitsman and Bakker 1996, Bailey 1998, Jia, et al. 2003, etc.). Detailed literature reviews in this field can be found in the papers of Comstock et al. (1999), Reddy et al. (2001) and Arthur et al. (2001). Examples of more recent research works in the investigations of optimal control of chiller systems include the works of Wang (2001), Massie (2002) and Chang (2004), etc.

It is worth noting that the performance of both the FDD methods and the optimal control strategies depend heavily on the quality of the measurements from sensors as concluded in the IEA project, Annex 34 (Computer Aided Evaluation of HVAC System Performance). Moreover, the continuous and accurate measurements of temperature, flow rate, electrical power, refrigerant pressure, etc., are also essential to safety interlocks of chiller system, quantification of effectiveness of energy-efficiency improvement (Phelan, J. et al. 1997), monitoring of chiller efficiency (Hartman T. B. 2001). Basically, errors or faults in measurements can be divided into two main categories called noise error which is the random fluctuating component of the total error and bias error which is the fixed the total error and is the main concern in this paper. When sensor faults, especially bias errors, exist, it is impossible and difficult to implement the above FDD, control, monitoring and optimization as the faulty sensors misrepresent the true conditions of the chiller system.

Research on sensor fault detection and diagnosis (sensor FDD) in HVAC systems has been very active in recent years (Stylianou et al. 1996, Wang et al. 1999 etc.). Most methods aimed at detecting/diagnosing part of the sensors in the systems. Validating all the sensors is a much weightier and more complicated task. More recently, Wang and Xiao (2004) developed a strategy based on PCA for the fault diagnosis of sensors in AHUs (air handling units). However, published research on sensor FDD within chillers cannot be found until now. In centrifugal chiller systems, temperature, pressure and power measurements are the measurements of main concern. Usually the variations of these measurements in large-sized water cooled chiller systems are relatively small when compared with those in other HVAC applications, which are more susceptible to the ever-changing environmental conditions. Moreover, these measurements are heavily correlated with one another due to the cycling of refrigerant which interacts with compressor, chilled and cooling water in the system. PCA's strong capability of capturing the correlations among a number of variables is particularly suitable to be used for sensor fault diagnosis and validation in chiller systems. As for component FDD in chiller systems, model-based methods are preferable to other ones in FDD applications and therefore show great potential in engineering applications (Yongzhong Jia, et al. 2003).

However, it is rather difficult to determine proper model structures which are simple, robust and physically explainable as well. Another fundamental issue in FDD application is to set appropriate threshold values. The threshold for fault detection is usually determined empirically or experimentally without conscientious analysis, which may not sensitive to some existing faults or produce false alarms.

This paper presents a heath monitoring package for centrifugal chiller systems. This package includes two FDD strategies, among which one is for sensors and the other is for component. The PCA-based sensor FDD strategy uses the *Q*-statistic as the indexes of sensor fault detection, and use the *Q*-contribution plot to isolate sensor faults, and to validate measurements of great concern. After that, the component FDD strategy, which is based on simplified reference models of six performance indexes, employ a threshold generator for fault detection to diagnose component degradation. Therefore the combined implementation of the two strategies can help realize the health monitoring and continuous commissioning of centrifugal chiller systems. Chiller measurements from a BMS are used to not only train the PCA model and reference models of performance indexes, but also to evaluate the capability of the two strategies to detect, diagnose and estimate the introduced sensor faults and existing component faults.

2. SENSOR FDD IN CENTRIFUGAL CHILLER SYSTEM USING PCA

2.1. Outline of PCA method in FDD

PCA is a multivariate statistical analysis technique (Edward 1991). By projecting the original correlated data into a lower-dimensional space using linear transformations, PCA can separate the observation space into a subspace capturing the systematic variations of the process and a subspace containing the random noise. A training data set of *n* observations and *m* process variables is assumed in the following to illustrate the principle of using PCA method for FDD application. Because variables in engineering systems usually have different units, these data are transformed into standard units by subtracting from each observation its mean and dividing by its standard deviation. The transformed data set will be denoted by sample matrix X ($X \in \Re^{n\times m}$). Solve an eigenvalue decomposition of the sample covariance matrix *S*,

$$S = \frac{X^T X}{n-1} = U \Lambda U^T \tag{1}$$

Where the Λ is a diagonal matrix of non-negative real eigenvalues with decreasing magnitude ($\lambda_1 > \lambda_2 > \ldots > \lambda_m$) and U is a matrix whose columns are the corresponding eigenvectors ($UU^T = I$). In order to optimally capture the variations of the data while minimizing the effect of random noise corrupting the PCA representation, only these eigenvectors in *U*, which are associated with the first *a* largest eigenvalues, are retained in PCA model. Selecting the columns of the loading matrix P ($P \in \Re^{m\times a}$) to correspond to the above loading vectors, the projections of the observations in *X* into the lower-dimensional space V ($V \in \Re^{m\times a}$), called score matrix, are shown by equation (2). Equation (3) shows the projection of *Y* back into the m-dimensional observation space, $\hat{X}$, which is called score space and an accurate representation of *X* while assuming PP^T captures the systematic variations.

$$V = XP \tag{2}$$

$$\hat{X} = VP^T = XPP^T \tag{3}$$

For a new observation *x* (row vector), the difference between *x* and its estimate $\hat{x}$ ($\hat{x} = xPP^T$) is the residual vector *e* ($e = x - \hat{x} = x(I - PP^T)$), which is also a projection of *x* into its residual space. Therefore, the observation *x* can be decomposed into two orthogonal vectors, which are *x* in score space and *e* in residual space.

In FDD applications of PCA, faults can be detected more robustly by using the Q-statistic, as shown by equation (4).

$$Q - statistic = SPE = e^T e = \|x - \hat{x}\|^2 = \left\|x\left(I - PP^T\right)\right\|^2 \le Q_\alpha \tag{4}$$

Where, Q_α is the threshold for the SPE and can be statistically determined (Edward, 1991). When there is no fault, the *Q*-statistic will be less than Q_α . When faults exist, the correlation among the measurements of the variables will be destroyed and a value of SPE higher than Q_α will be detected. Once a fault normal is detected, the next step is fault diagnosis whose aim is to determine which process variables are most relevant to the occurred faults, therefore focusing the operators on the place where the faults occurred. Finally the task of sensor fault validation is to estimate the normal value (x^*) of observation vector (row), as good as possible, using the observed vector *x*, the constructed PCA model and the detected fault direction. The reconstructed vector, $\overline{x}$, is obtained by minimizing the SPE of $\overline{x}$ (Dunia et al. 1996), and then the bias errors with the observed vector can be estimated.

2.2. Sensor FDD strategy based on PCA

Centrifugal chiller system and sensors

Considering the fact that there are a great number of sensors in a typical centrifugal chiller system, the most essential sensors for system stable and optimal operation are herein selected first of all, which are listed in Table 1. Both the chilled water supply temperature and the entering condenser water temperature vary in a small range because these two variables are well under control all the time. In addition, the water flow rates through condenser and evaporator are maintained to be constant for stable and safe operation of the heat exchangers in most engineering applications. It is generally accepted that the flow rates and temperatures of chilled water (T_{chws} and M_{chw}) as well as those of cooling water (T_{ecw} and M_{cw}) are the driving conditions of a specific chiller system (J.E. Braun 1988 and PG&E 2001). It is not difficult to understand that PCA model can capture the systematic trend of the chiller system because the variations of driving conditions are small.

Table 1. Sensors of great concern in a centrifugal chiller system

Sensor	Description	Unit	Sensor	Description	Unit
T_{chws}	Chilled-water supply temperature	°C	T_{ev}	Evaporating temperature	°C
T_{chwr}	Chilled-water return temperature	°C	P_{ev}	Evaporating pressure	Pa
M_{chw}	Chilled-water flow rate	L/s	T_{cd}	Condensing temperature	°C
T_{ecw}	Entering condenser water temperature	°C	T_{dis}	Compressor discharge temperature	°C
T_{lcw}	Leaving condenser water temperature	°C	P_{ev}	Condensing pressure	Pa
M_{cw}	Condenser water flow rate	L/s	W_{elec}	Chiller electrical power input	kW

PCA models based on thermodynamic knowledge

Two PCA models were here constructed and deduced considering thermophysical characteristics of chiller systems. As shown in equation (11)-(16), some performance indexes can describe health conditions of a chiller system. These performance indexes are not constants but functions of such driving conditions as water temperatures and flow rates. It might be concluded that the variables involved in the above performance indexes are correlated with each other. The PCA model based on performance correlation (model A) is hereby obtained, containing 9 variables: T_{chws}, T_{chwr}, T_{ev}, P_{ev}, T_{lcw}, T_{ecw}, T_{cd}, P_{cd} and T_{dis}, which are available on BMS.

$$A = [T_{chws}, T_{chwr}, T_{ev}, P_{ev}, T_{lcw}, T_{ecw}, T_{cd}, P_{cd}, T_{dis}] \tag{5}$$

With respect to the refrigeration cycle at steady state, the net change in the internal energy of the chiller refrigerant after a complete cycle is zero as the internal energy is a state function. From the first law of thermodynamics, one can obtain:

$$W_{elec} Eff_{motor} + M_{chw} C_{pw} (T_{chwr} - T_{chws}) - M_{cw} C_{pw} (T_{lcw} - T_{ecw}) = 0 \tag{6}$$

Where W_{eek} is the electrical power input to the compressor motor. C_{pw} is water specific heat. Eff_{motor} is drive motor efficiency which is a function of driving conditions, e.g., cooling load and water temperatures. M_{chw} is the chilled water flow rate and M_{cw} is the condenser water flow rate. T_{chws} is the chilled water supply temperature. T_{chwr} is the chilled water return temperature. T_{ecw} is the entering condenser water temperature. T_{lcw} is the leaving condenser water temperature.

Therefore, the PCA model based on energy balance (model B) involves 7 variables: W_{elec}, M_{chw}, T_{chws}, T_{chwr}, M_{cw}, T_{ecw} and T_{lcw}, which are also available BMS. This model can detect faults in 7 sensors in the chiller system.

$$B = [T_{chws}, T_{chwr}, M_{chw}, T_{lcw}, T_{ecw}, M_{cw}, W_{elec}] \tag{7}$$

2.3. Validation test of sensor FDD in a real chiller system

The PCA-based sensor FDD strategy was tested using measurements from an existing BMS in a commercial building in Hong Kong. Chiller data were collected, during a period of a month, from a 1,540 ton (5,400 kW) York seawater cooled centrifugal chillers in Dorset House Hong Kong. Since the chiller system just went through a routine process of re-commissioning, healthy and fault-free operations of the components, sensors, controller, actuator, etc., could be ensured. The collected data sets could hereby be thought to have the capability to describe the fault-free operation of the plant. The noise errors associated with individual measured data was assumed to be Gaussian distribution with mean zero and standard deviation half of the measurement accuracy.

The data of three days, from July 4th to 6th were employed in the testing. The data from the first two days were used for PCA model training and the data from the last day were added with biases for testing the fault detectability and isolability of PCA model. In this study, the number of retained loading vectors, namely the number of principle components (PCs), is determined by the percent variance method. In this study, 3 and 4 loading vectors are respectively retained in the two models. Subsequently two detection thresholds of Q-statistic with a certain confidence level were also determined for the two models, respectively. After model training, 156 samples indicative of steady state operation on July 6th, were added with pre-determined biases in order to generate typical faulty sensors for testing the sensor FDD method based on PCA. Only one sensor was added with bias at each test. Due to the limitation of space, only the tests for PCA models based on performance correlation (model A) are presented in this paper. Table 2 shows the magnitude of the biases and the sample range affected in the tests.

Table 2. Biases added to the samples obtained under normal sensor conditions on July 6th

	T_{ev}	P_{ev}	T_{cd}	P_{ev}	T_{dis}
Bias	2°C	50kPa	3°C	100kPa	5°C
Sample range	21-40	41-60	61-80	81-100	101-121

Figure 1 shows the Q-statistic plot of the samples in the tests. It shows that nearly all the Q-statistics values were above the threshold while five pre-determined biases, i.e. δT_{ev}, δP_{ev}, δT_{cd}, δP_{cd} and δT_{dis}, existed in the corresponding sensors. The sensor faults were successfully detected. Figure 2 shows the test results of sensor fault diagnosis using a Q-contribution plot in the tests. Note, the test results of different sensor faults are illustrated in one figure to reduce the need of space. The Q-contribution plot could help to find the sensors with biases successfully. The biases of the faulty sensors in the tests were estimated correctly by sensor fault reconstruction and the results are shown in table 3, where the comparison between the introduced biases and the estimated ones is also provided. It could be observed that most of the introduced sensor biases can be estimated precisely with relative estimation errors lower than 10%. Therefore, the proposed sensor FDD strategy based on PCA for centrifugal chiller system is capable to detect/diagnose and validate faulty sensors.

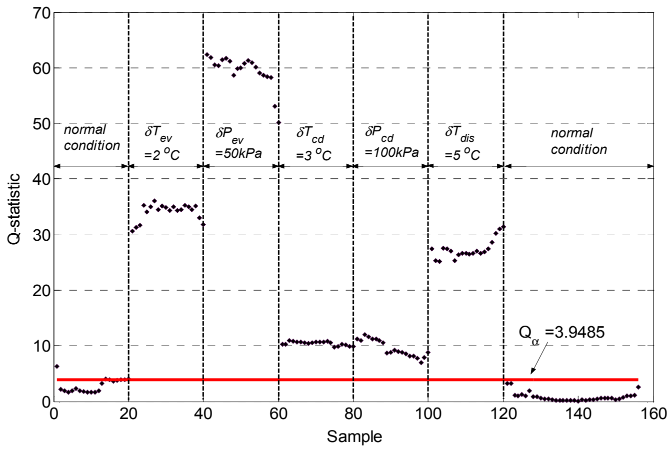

Figure 1. Q-statistic plot of the tests using model A – faulty sensors: T_{ev} , P_{ev} T_{cd} P_{cd} and T_{hg}

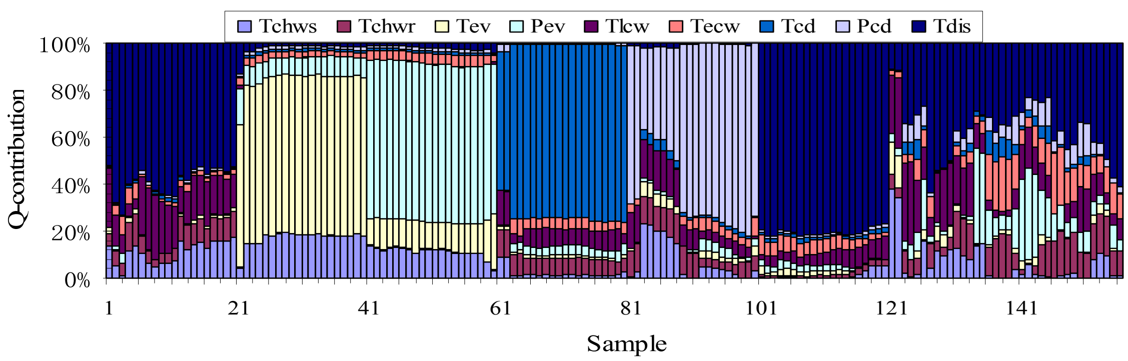

Figure 2. Q-contribution plot of the first tests using model A – faulty sensors: T_{ev} , P_{ev} T_{cd} P_{cd}

Table 3. Results of sensors fault validation

	T_{ev}	P_{ev}	T_{cd}	P_{ev}	T_{dis}
Introduced Bias	2℃	50kPa	3℃	100kPa	5℃
Estimated bias	2.1℃	52.4kPa	3.3℃	105.7kPa	5.4℃
Relative error	5.4%	4.8%	9.1%	5.7%	8.6%

3. MODEL BASED COMPONENT FDD FOR CENTRIFUGAL CHILLER SYSTEMS

3.1. Basic approach

The FDD strategy developed in this study comprises a steady-state filter, performance index generators, reference models and online threshold estimator. Six performance indexes are selected as the indicators of different faults. The amount and the patterns of the performance indexes are interpreted to identify faulty operating conditions and diagnose, if possible, which components are faulty. The benchmark quantities of the performance indexes are provided by the reference models in the form presented in equation (8), assuming that the mean and variance of the error term are zero and σ^2 respectively (i.e. $\varepsilon \sim N(0, \sigma^2)$) (Montgomery and Runger 1994).

$$Y = f(Q,\theta) + \varepsilon = b_1 Q + b_2 Q\theta + b_3\theta + b_4 + \varepsilon \tag{8}$$

Where, the above temperatures are based on Kelvins, and $\theta = T_{ecw}/T_{chws}$. The two selected independent variables, Q and θ, are the cooling load and the ratio of the entering condenser water temperature to the chilled water supply temperature respectively. The reason behind such selection is that the correlations between the performance indexes and these two independent variables are strong, which will be shown in table 5. The simple structure of the regression models ensure that they can be accurately and conveniently identified.

The data from BMS interfaced with chiller control panels are collected with certain intervals. Once the data pass through the steady-state filter, which are considered representing the chiller performance under steady-state operation, all performance indexes at this sampling instance are calculated. Meanwhile the reference quantities of the performance indexes are calculated by the corresponding reference models. The residual for each performance index is generated by comparing the calculated value from the generator of a performance index with that predicted by its corresponding reference model. Each residual is compared with its threshold in the residual evaluation stage.
Another important feature of the method is that fault diagnosis is conducted at the same time of the fault detection as the five of the performance indexes are corresponding to five different component/subsystem faults except the chiller COP of the chiller, which is an overall performance indicator. When the performance of a component/subsystem (or more than one subsystem) degrades to a certain extent, the corresponding performance index will deviate from its (their) reference value, a component fault is detected and diagnosed. In the mean time, the overall performance COP will also deviate from its reference value, which enhances the reliability of the FDD output.

It is worth noting that the threshold for the residual of a performance index is updated online using the uncertainty of the estimated residual, which is contributed by both model fitting errors and measurement errors associated measurements from BMS, as illustrated by equation (9). Where, $Th_{0,i}$ is the threshold of the i_{th} performance index, $\tilde{r}_i$ is the residual of the *ith* performance index, $U(\cdot)$ is the uncertainty at a certain confidence level . The existence of faults are therefore detected and diagnosed in the classifier which correlates the violation of a performance index with a specific component fault type (see table 4). The detailed procedures are explained in the following subsections.

$$Th_{0,i} = U(\tilde{r}_i) = t_{\alpha/2, n-2}\,\tilde{\sigma}_{\tilde{r}_i - r_i} \tag{9}$$

Where, $\tilde{\sigma}^2_{\tilde{r}_i - r}$ is obtained by equation (10) and eventually used for FDD in this study. $t_{\alpha/2, n-2}$ is the value of the t distribution with n-2 degrees of freedom at a confidence level of $(1-\alpha)$, n is the number of training data set for reference model fitting, p is the number of independent variables in reference models.

$$\tilde{\sigma}^2_{\tilde{r}_i - r_i} = \sum_j \left[\left(\frac{\partial g_i}{\partial z_j}\right)\sigma_{z_j}\right]^2 + \tilde{\sigma}^2_{Y_i}[1 + x_0^T (X_{reg}^T X_{reg}) x_0] \tag{10}$$

Where, g_i and f_i are respectively the calculation formula and reference model of the ith performance index. z_j is the j_{th} element in the vector of measured variables used to calculate the ith performance index. σ_{z_j}, σ_Q and σ_θ are standard deviations of z_j, Q and θ respectively. $\tilde{\sigma}^2_{Y_i}$ is the estimated variance of the regression error of ith performance index Y_i. x_0 is the vector of independent variables where uncertainty is calculated. X_{reg} is the matrix of independent variables used in the identification of reference models. X^T_{reg} is the transformed matrix of X_{reg}. The deduction of equation (10) is omitted in this paper due to space limitation.

3.2. Performance indexes of centrifugal chillers

Performance indexes sensitive to particular faults are used in this study to indicate the health condition of corresponding components in chiller systems. Six performance indexes are selected in this study to describe the operation characteristics. The physical meanings of the performance indexes and the correlation between performance indexes and fault types are summarized in table 4.

The mathematical formulations of the performance indexes, shown in equation (11)-(16), are developed on the basis of the following assumptions made on a standard one-stage refrigeration cycle: *(i).* Adiabatic compression in the centrifugal compressor; *(ii).* Heat rejection at constant refrigerant pressure in the flood type condenser; *(iii).* Heat absorption at constant refrigerant pressure in the flood type evaporator; *(iv).* Isenthalpic throttling through the orifice plate. Obviously the mathematical formulations derive from fundamental thermodynamic or heat transfer considerations. Therefore, the performance indexes can be determined directly from measurements available on BMS no matter the chiller system is faulty or fault-free. Because the indexes are almost independent, e.g. logarithm mean temperature differences of evaporator and condenser, the fault detection and diagnosis can be conducted simultaneously by means of the performance indexes with strong thermophysical meanings. It is noteworthy that all the above equations are valid in steady-state condition only. Since large chillers operate in quasi-steady-state during most of their operating time, the validity of the models can be justified.

Table 4. The relationship between performance indexes and fault types

Formulation	Physical meaning	Fault Type
$LMTD_{ev} = \dfrac{T_{chwr} - T_{chws}}{\ln\left(\dfrac{T_{chwr} - T_{ev}}{T_{chws} - T_{ev}}\right)}$ (11)	logarithm mean temperature difference of condenser	degradation of evaporator
$LMTD_{cd} = \dfrac{T_{lcw} - T_{ecw}}{\ln\left(\dfrac{T_{lcw} - T_{cd}}{T_{ecw} - T_{cd}}\right)}$ (12)	logarithm mean temperature difference of evaporator	degradation of condenser
$M_{ref} = \dfrac{C_{pw} M_{chw} (T_{chwr} - T_{chws})}{h_1 - h_4}$ (13)	mass flow rate of refrigerant	liquid restriction, refrigerant leakage
$V_{ref} = \dfrac{C_{pw} M_{chw} v_{in} (T_{chwr} - T_{chws})}{h_1 - h_4}$ (14)	volume flow rate of refrigerant at compressor impeller inlet	degradation of inlet guide vane
$Eff_{motor} = \dfrac{M_{ref}(h_2 - h_1)}{W_{elec}}$ (15)	drive motor efficiency	degradation of drive motor
$COP = \dfrac{C_{pw} M_{chw} (T_{chwr} - T_{chws})}{W_{elec}}$ (16)	coefficient of performance	degradation of overall system performance

(where, h_1-h_4 is the specific refrigeration quantity, h_2-h_1 is the specific internal power consumption of compressor, v_{in} is the specific volume of refrigerant at the compressor impeller inlet.)

3.3. Validation tests of component FDD strategy on a real chiller system

<u>*Training of reference models*</u>

The field-monitored chiller data on July 4th, 2001 from the same chiller system mentioned in section 2.3 were used to identify the reference models. Similarly, the data, used for the parameter identification, went through a well calibrated steady-state filter first. The correlations between the independent variables (Q, θ) and the performance indexes ($LMTD_{ev}$, $LMTD_{cd}$, M_{ref}, V_{ref}, Eff_{motor}, COP) are presented in table 5. Generally speaking, the correlations are strong, especially the correlation between the above response variables and Q. An exception is that correlation coefficient between $LMTD_{ev}$ and θ was 0.3957 which was low. The reference models with two independent variables in the form of equation (8) were identified with the constant coefficients found by the least square error estimation. The results are summarized in table 6. Maximum CV% less than 11.8% and minimum R^2 larger than 76.58% are two more indicators showing a strong goodness of fit of the regression models

Table 5. Correlation coefficients for independent and response variables in models during training

	$LMTD_{ev}$	$LMTD_{cd}$	M_{ref}	V_{ref}	Eff_{motor}	COP
Q	0.7997	0.9716	0.9996	0.9920	0.9828	0.9518
θ	0.3957	0.7677	0.7718	0.7334	0.7303	0.6229

Table 6. Regression statistics of the performance index models trained with field-monitored data

	$LMTD_{ev}$	$LMTD_{cd}$	M_{ref}	V_{ref}	Eff_{motor}	COP
CV% (coefficient of variation)	11.83%	4.14%	1.81%	0.61%	1.86%	1.63%
R^2 (coefficient of determination)	76.58%	94.99%	99.99%	98.93%	96.87%	93.75%

Validation tests of strategy

The measurements of 35 days collected after July 4th 2001 (the day used for model training) were used to validate the strategy. In the first 20 days, no abnormal performance was detected by the strategy. After July 24th 2001 (21 days after the commissioning), the strategy started to detect abnormal performances and the abnormal performance detected became serious gradually. The test results using the data collected on July 31st 2001 (28 days after system commissioning and calibration) were presented here to illustrate the performance of the FDD strategy.

When the FDD method was implemented in developing the strategy, the measured performance indexes at steady-state were compared with the model predicted values. Results are presented in figure 3. The solid lines indicate the threshold band, which is determined by the estimated uncertainty values updated by equation (9) with 99.7% confidence using online measurements. Only if a performance index residual goes beyond the threshold band, one would regard the performance point as a fault. Otherwise the chiller system is assumed to be fault-free (normal). It is obvious in figure 3-(2) and 3-(6) that most of measurements were identified as faulty. The overall performance of the chiller degraded. The residuals of the $LMTD_{cd}$ of the condenser increased beyond the ever-updating thresholds, indicating reduction in heat transfer efficiency. In contrast, the residuals of $LMTD_{ev}$ never went beyond its thresholds. The reason here is that the condenser of the centrifugal chiller is directly cooled by seawater and the evaporator was serviced by well preprocessed cycling freshwater. The corrosion and fouling of the condenser, without purging during the following period, developed gradually. The degraded *COP* was the result of the fact that fouling of condenser inevitably reduced system efficiency. Though the test results presented in this field test are limited to faults of heat exchanger fouling, the FDD method can apply to other chiller faults as the underlying concepts can still be of practical relevance as to them.

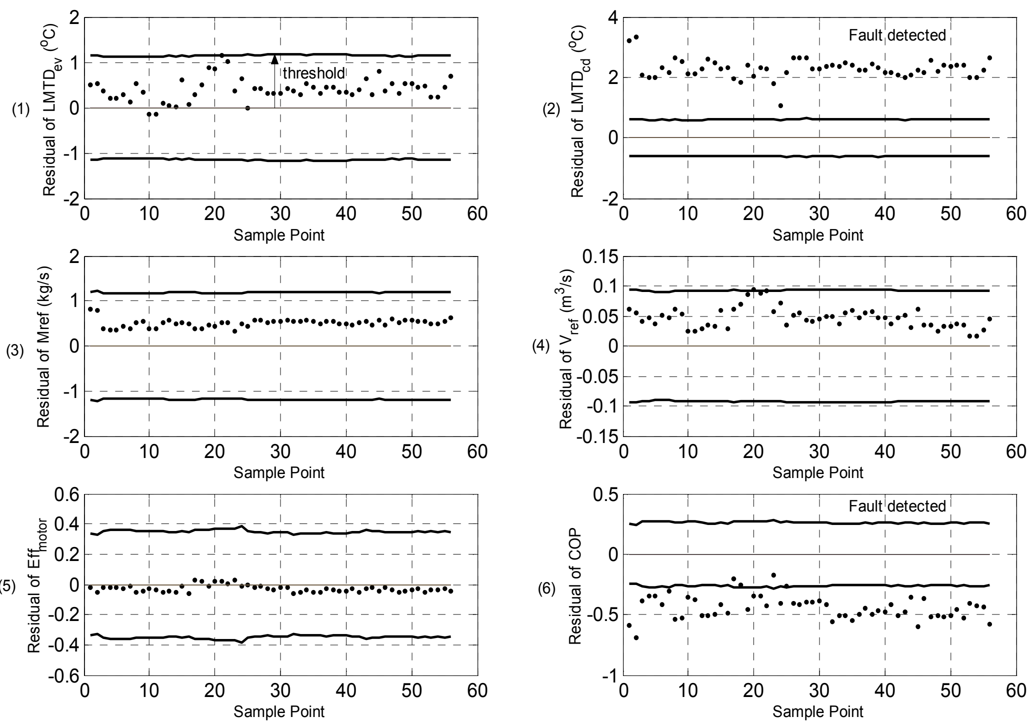

Figure 3 Detection of degradation of evaporator and condenser with field-monitored chiller data (56 steady-state sets on July 31st 2001)

4. CONCLUSIONS

The testes show that the sensor FDD strategy can detect, diagnose and reconstruct sensor faults successfully. PCA models, on which the sensor FDD strategy is based, can group variables of great correlation, capture the systematic trend, and therefore provide a good means of generating useful residuals for sensor FDD in centrifugal chiller systems. The component FDD strategy can classify faults into the component level of centrifugal chiller system. Furthermore, the threshold of fault detection is determined by conscientious uncertainty analysis, which shows that thresholds should vary according to the change of operating condition. Studies also indicate that the validity and sensitivity of the component FDD strategy are heavily dependent on the measurement quality. It justifies the needs of combining the component FDD strategy with a sensor FDD strategy. The simple structure of the models for performance indexes enables them to be easily trained and conveniently implemented in applications.
It is worth pointing out that a third strategy is needed, in the case that both strategies report faults, to help the commissioning of chiller systems. In addition, the two FDD strategies should be evaluated using more field data indicative of faulty measurements or components of centrifugal chillers.

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